

# Análise de séries temporais

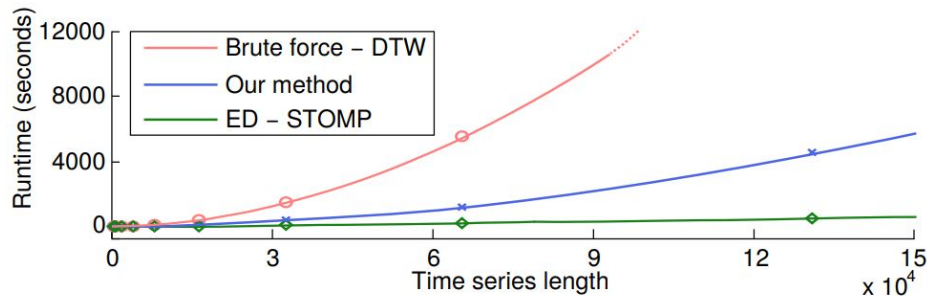
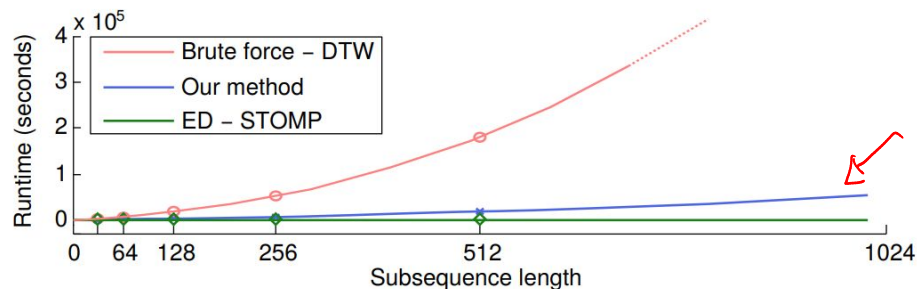
por similaridade e alinhamento não  
linear com Dynamic Time Warping



# MP com DTW

$O(\ell n^2)$   
 $O(\ell^2 n^2)$   $\Rightarrow$  problema  $\ell$  costuma ser grande

A primeira tentativa foi adaptar o UCR-USP Suite (com PSI)



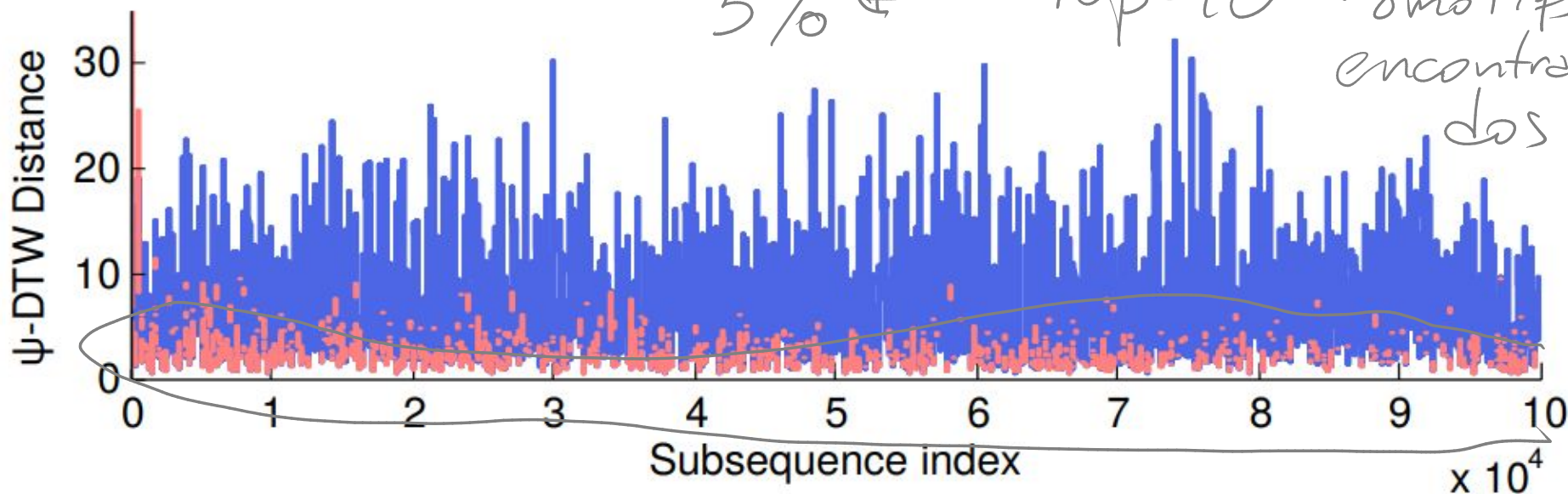
# MP com DTW

Mais lento, mas muito mais significativo

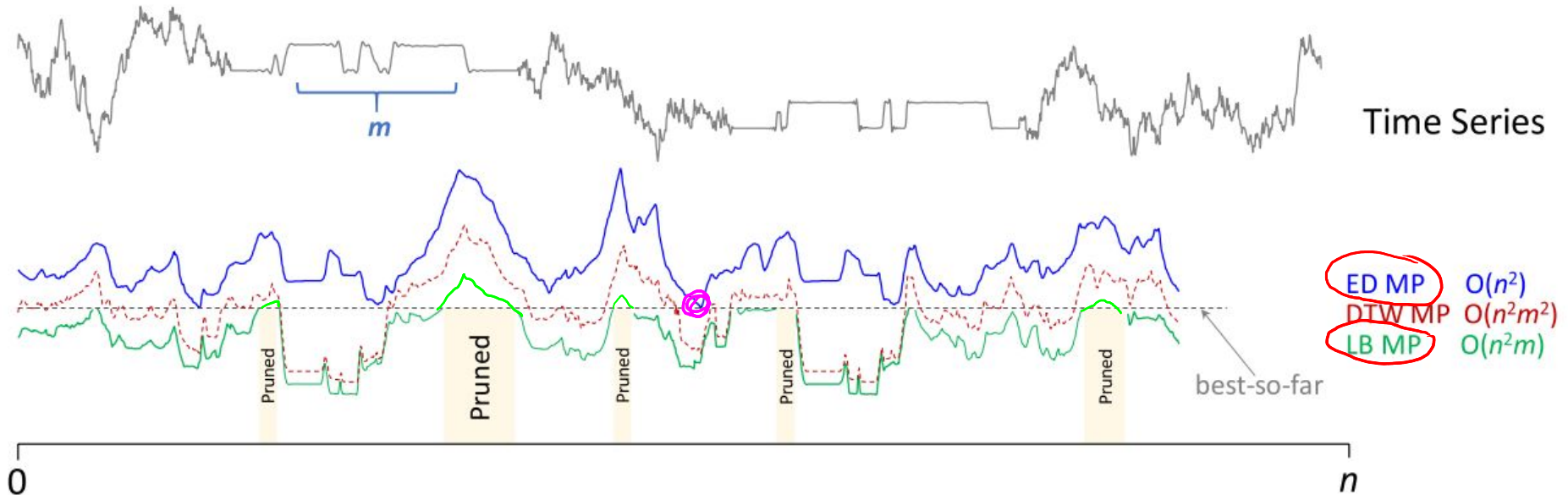
- Tende a achar padrões menos “flat”
- Não assume como discord uma subsequência com vizinho próximo, mas com pequeno *warping*
- Não descarta motif por conta de prefixos e sufixos

# MP com DTW - mais eficiente para motivos

5% ← top-10 → 8 motivos encontrados



# MP com DTW - mais eficiente para motivos



# Outras variações

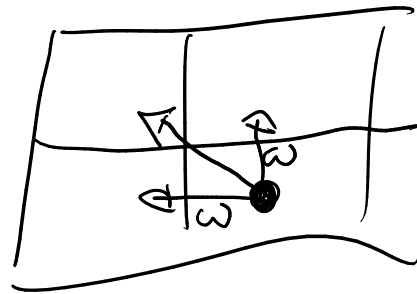
# Weighted Slope DTW

Adicionamos um peso aos passos “não-diagonais”

$$dtw(i, j) = c(x_i, y_j) + \min \begin{cases} dtw(i-1, j) \cdot w \\ dtw(i, j-1) \cdot w \\ dtw(i-1, j-1) \end{cases}$$

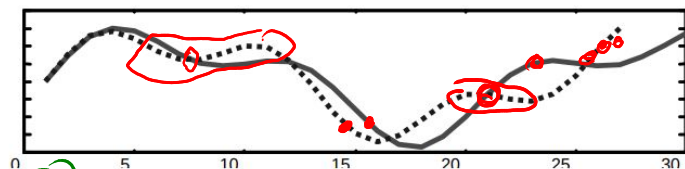
$w > 1$

Também é possível fazer outros tipos de ponderação

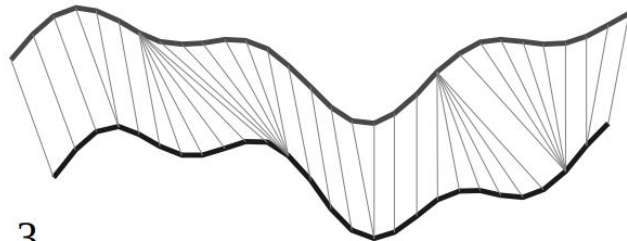


# Derivative DTW

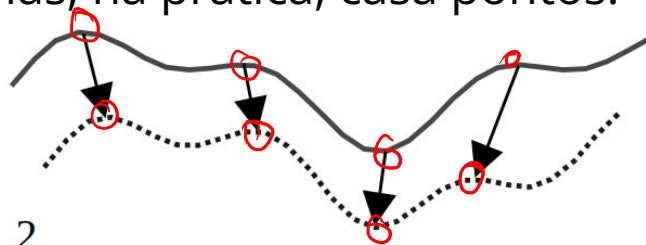
A princípio, DTW deveria “casar formatos”. Mas, na prática, casa pontos.



1



3



2




4

**Figure 6:** 1) Two artificial signals. 2) The intuitive feature to feature warping alignment. 3) The alignment produced by classic DTW. 4) The alignment produced by DDTW.



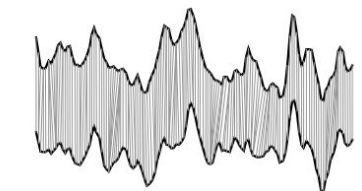
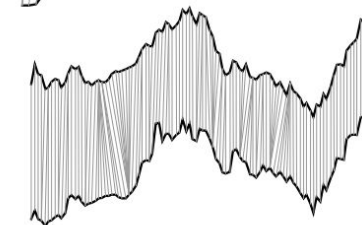
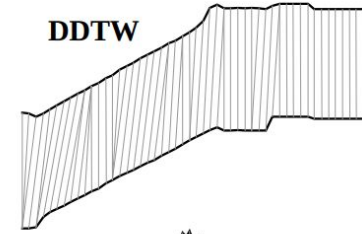
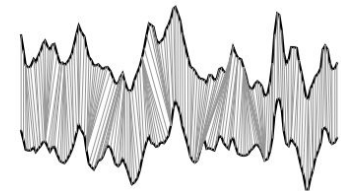
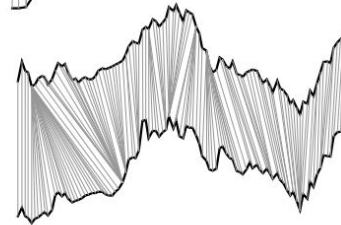
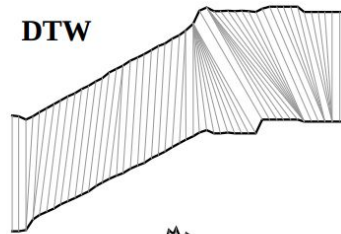
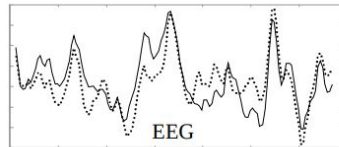
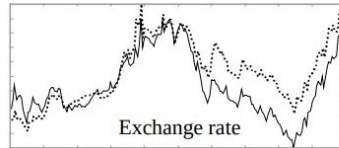
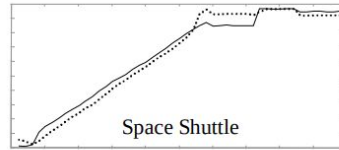
# Derivative DTW

A DDTW apenas estima a derivativa antes de fazer o alinhamento:

$$D_x [q] = \frac{(q_i - q_{i-1}) + (q_{i+1} - q_i)) / 2}{2}$$


# Derivative DTW


+ exemplos



# Metric DTW

## Metric learning

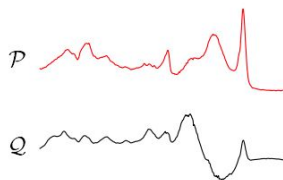
Mas o que exatamente são “shapes” que deveriam casar?

- Talvez dependa do domínio. 
- Podemos aprender com os próprios dados, então?
- Alguns trabalhos propõem aprender uma medida para substituir a euclidiana como custo

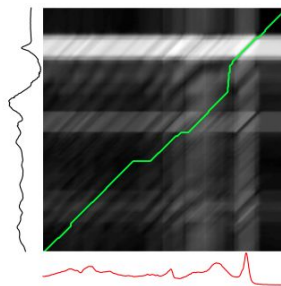
# Metric DTW

$$c(x_i, y_j) = (x_i - y_j)^2$$

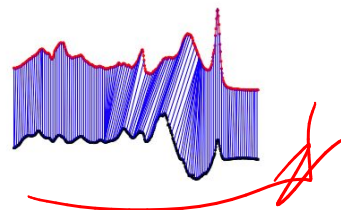
(a) input sequences



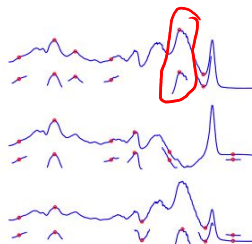
(b) DTW alignment path  $\mathbf{p}$



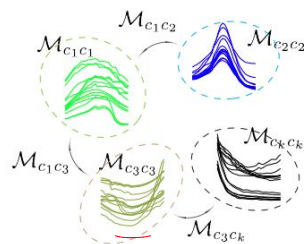
(c) DTW alignment



(d) temporal point descriptors



(e) descriptors clusters

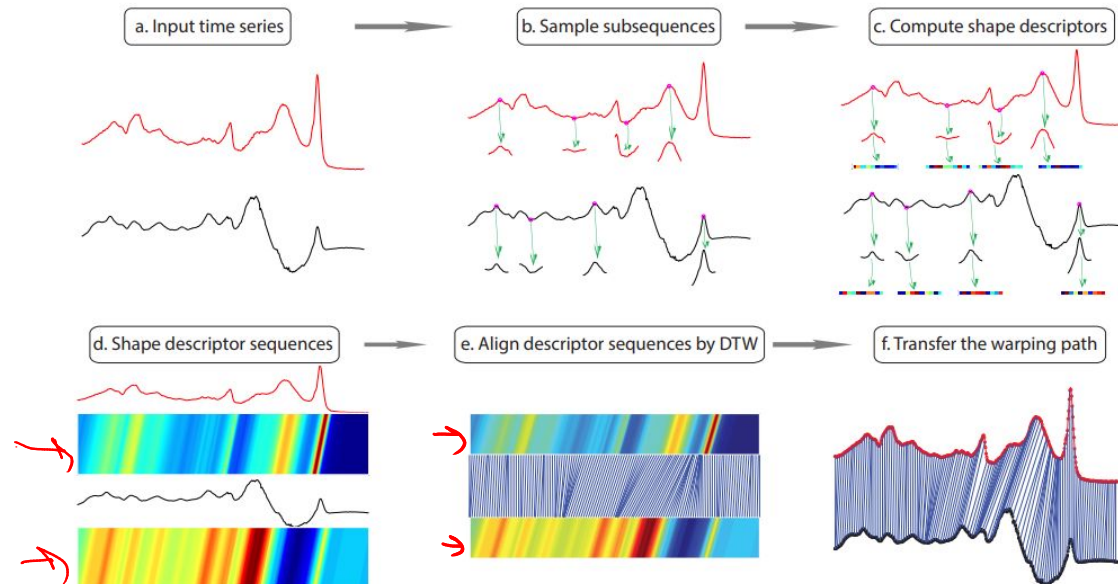


(f) DTW distance under learned metrics

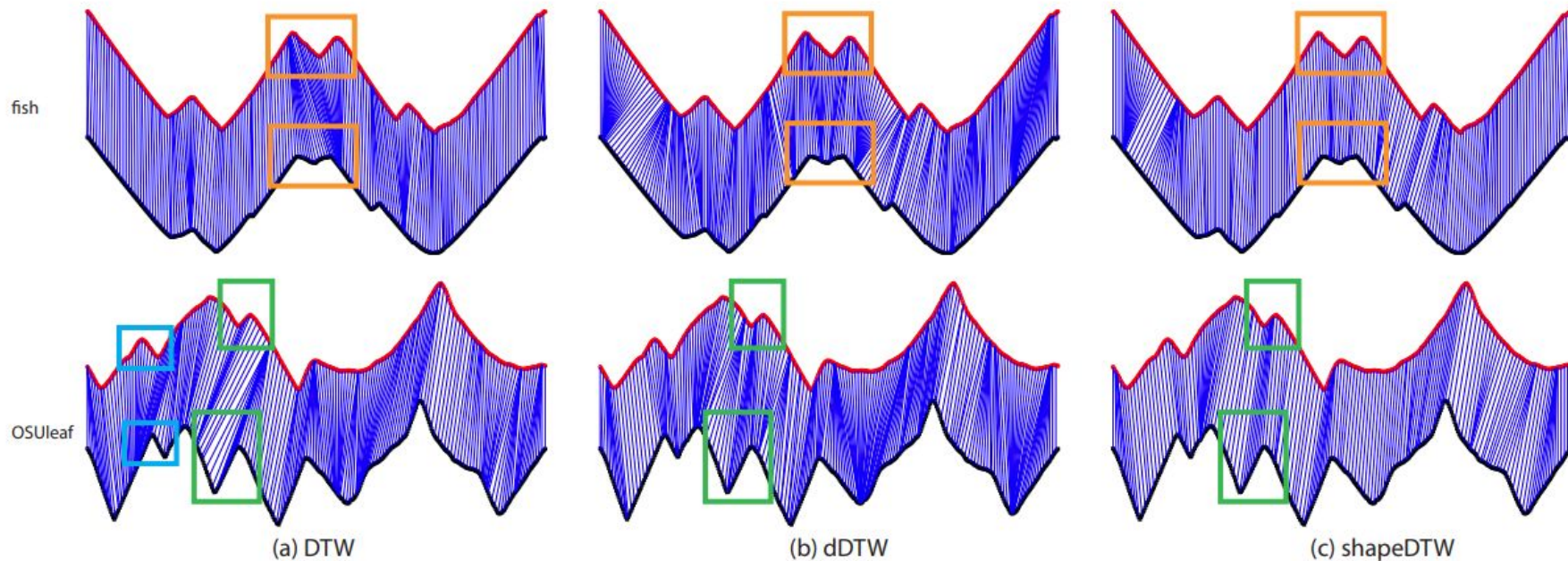
$$D(\mathcal{P}, \mathcal{Q}) = \sum_{(i,j) \in \mathbf{p}} (\vec{p}_i - \vec{q}_j)^T \mathcal{M}_{c_i c_j} (\vec{p}_i - \vec{q}_j)$$

# ShapeDTW

Extrai descritores de *shape* e os alinha com DTW

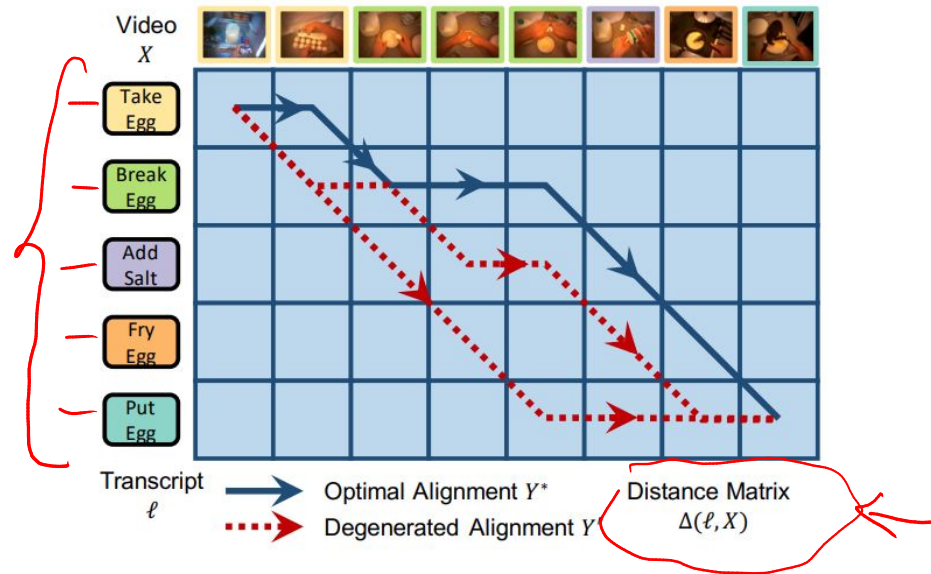


# ShapeDTW



# D3TW

um exemplo de matriz de custo que não tem nada a ver com distância



# Derivative DTW

Para não dizer que não fizemos nada aqui, façam um exercício

- Utilizem o notebook de alinhamento que vocês fizeram
- Criem um método para calcular a derivativa (DDTW)
- Alinhem as séries
- Plotem o resultado e comparem com a DTW padrão

$$D_x [q] = \frac{(q_i - q_{i-1}) + (q_{i+1} - q_i)}{2}$$
